CHAPTER 5
CLASSIFIER BASED RECOMMENDER SYSTEMS FOR STOCK TRADING

5.1 Introduction

Time series forecasting based stock trading recommender system presented earlier, demonstrated better time series forecasting accuracy when compared to the conventional approach of selecting the entire dataset for training. It was also observed that the trading rule, which generated the buy/sell recommendations from the forecasts, had a significant influence on the economic returns generated by the system. Even though the trading rules employed for the purpose were quite simple and were able to generate returns better than the naïve B&H strategy, the system still requires intervention from the end user as far as the design of the trading rule is concerned. In this chapter, an alternative approach to designing a stock trading recommender system is presented, which attempts to address this issue. Novelty of the approach presented in this chapter is that it employs classification techniques for the purpose. The proposed systems convert the issue of generating trading recommendations, typically viewed as a regression problem, into a classification problem. It is also observed from the literature survey in chapter 2, that stock trading decision support/ recommender systems employing classifiers for forecasting trends in financial data or to generate trading rules have not received much attention. The feasibility of classification based techniques for developing a stock trading recommender system has been explored in this chapter.

Technical indicators have been traditionally used for identifying trends in the market and for identifying overbought/oversold stocks, eg. in (Eng, 1988) and (Achelis, 1995). However, the major issue with a technical analysis based trading strategy is that the selection of the optimal set of technical indicators, their parameters and the identification of buy/sell points under the given market condition, is still performed subjectively, based on the skill and experience of the trader. Hence, a stock trading recommender system which can utilize technical indicators, while at the
same time, eliminate requirement for any ‘expert’ knowledge on the part of the user is likely to be of great help to a novice trader who wish to gain profit by trading in stocks. For this purpose, the recommender system should operate at a high level of abstraction, ie. it should be capable of automatically selecting the optimal set of technical indicators as well as their parameters while generating an unambiguous buy/sell recommendation as the output.

In this chapter, design of two different stock trading recommender systems designed using a classification based approach has been presented. The efficacy of the proposed systems is validated on four different stocks belonging to two different stock markets (India and UK) over three different time frames for each stock. Performance of the proposed system is validated using twelve different commonly used performance measures (Brabazon and O’Neill, 2006), (Nair and Mohandas, 2014), (Nair et al., 2013) and (Nair, Mohandas and Sakthivel, 2011). Performance is compared with traditional benchmark B&H strategy and technical analysis based trading.

The rest of the chapter is organized as follows: process used for selection of the input feature set is presented in section 5.2 and the generation of the decision table is detailed in section 5.3. The performance measures employed for validating the system performance are presented in section 5.4. Section 5.5 presents the design and results from the two classifier based recommender systems. Section 5.6 presents the results of the conventional traditional technical indicator based trading strategy. Conclusions are presented in section 5.7.

5.2 Selection of the input feature set

Identification of the size of training and test dataset is done using the technique similar to the one proposed in (Nair et al., 2013). The technique has been explained in section 3.2. Once the duration of the most prominent cycle (rounded to the nearest integer), $L$, is identified using the technique in 3.2, the number of samples in the test set (out-of sample) is fixed as $L$ assuming the continuation of the cycle for at least one cycle into the test set.

It was observed that the number of samples in the feature set, considering only $L$ samples, was too small to train the classifier; hence larger training sets composed of technical indicators extracted from samples with lengths in multiples of $L$, denoted by $M$, were evaluated. The multiple $M$ that resulted in the highest in-sample performance is denoted by $M_{opt}$. The multiple
\(M_{opt}\) was found to be different for different time frames, even for the same stock. Hence, a trial and error approach was used to find \(M_{opt}\) for each time frame. The final selected time frames consisting of \(M_{opt} \times L\) number of days in the in-sample data and \(L\) number of days in the out-of sample data are presented in Table 5.1.

<table>
<thead>
<tr>
<th>Table 5.1 Time frames for the selected stocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>Timeframe 1</td>
</tr>
<tr>
<td>In-sample</td>
</tr>
<tr>
<td>---</td>
</tr>
</tbody>
</table>

Initially, a set of thirty one randomly selected technical indicators are considered along with the closing price series. The technical indicators are selected from three broad categories, namely, volume based indicators, price based indicators and overlays. The technical indicators used in the present study are listed in Table 5.2. Detailed description of these technical indicators is widely available in literature, for eg. in (Achelis, 1995) and (Eng, 1988). Technical indicators used in this study along with the formulae required to calculate it and the typical technical indicator parameters are presented in table C.1 in Appendix C.
**Table 5.2 List of indicators used as the initial feature set**

<table>
<thead>
<tr>
<th>Feature No.</th>
<th>Indicator</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Negative Volume Index (NVI)</td>
<td>Volume-based indicators</td>
</tr>
<tr>
<td>2</td>
<td>Volume Rate of Change (VROC)</td>
<td>Volume-based indicators</td>
</tr>
<tr>
<td>3</td>
<td>On Balance Volume (OBV)</td>
<td>Volume-based indicators</td>
</tr>
<tr>
<td>4</td>
<td>Positive Volume Index (PVI)</td>
<td>Volume-based indicators</td>
</tr>
<tr>
<td>5</td>
<td>Price Volume Trend (PVT)</td>
<td>Volume-based indicators</td>
</tr>
<tr>
<td>6</td>
<td>Percentage Volume Oscillator consisting of two indices</td>
<td>Percentage Volume Oscillator (PVO)</td>
</tr>
<tr>
<td>7</td>
<td>Moving average of PVO (PVO_MA)</td>
<td>Percentage Volume Oscillator (PVO)</td>
</tr>
<tr>
<td>8</td>
<td>Relative Strength Indicator (RSI)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>9</td>
<td>Ease of Movement (EM)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>10</td>
<td>Highest High (HH)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>11</td>
<td>Lowest Low (LL)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>12</td>
<td>Moving Average Convergence Divergence consisting of two indices</td>
<td>Nine period moving average (NPMA)</td>
</tr>
<tr>
<td>13</td>
<td>MACD line (MACD)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>14</td>
<td>Momentum (MOM)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>15</td>
<td>Acceleration (ACC)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>16</td>
<td>Stochastic oscillator (ST) consisting of two indices</td>
<td>%K</td>
</tr>
<tr>
<td>17</td>
<td>%D</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>18</td>
<td>Ulcer index consisting of three indices (UIDX)</td>
<td>Ulcer index (UI)</td>
</tr>
<tr>
<td>19</td>
<td>moving average of UI (UI_MA)</td>
<td>Ulcer index (UI)</td>
</tr>
<tr>
<td>20</td>
<td>Percentage Drawdown (PD)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>21</td>
<td>Chaikin’s Volatility (CVOL)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>22</td>
<td>William’s %R (%R)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>23</td>
<td>Typical Price (TP)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>24</td>
<td>Price Rate of Change (PRoC)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>25</td>
<td>Median Price (MP)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>26</td>
<td>Weighted Close (WC)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>27</td>
<td>William’s Accumulation/ Distribution (WAD)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>28</td>
<td>Ultimate Oscillator (UO)</td>
<td>Price-based indicators</td>
</tr>
<tr>
<td>29</td>
<td>Bollinger (BOL) bands consisting of three indices</td>
<td>Bollinger Upper (BBU)</td>
</tr>
<tr>
<td>30</td>
<td>Bollinger Mid (BBM)</td>
<td>Overlays</td>
</tr>
<tr>
<td>31</td>
<td>Bollinger Lower (BBL)</td>
<td>Overlays</td>
</tr>
</tbody>
</table>
5.3 Generating the decision table

The selection of appropriate parameters for generating the technical indicators is dependent, to a large extent on the expertise of the trader. The proposed system uses GA to optimize the parameters of the technical indicators which are then given to a decision tree classifier to generate the ‘Trade’ or ‘No Trade’ recommendations.

Considering the feature set with ‘d’ number of features (technical indicators) represented using \( f_i \), for a total time frame of \( N \) days, the information table:

\[
I_{info} = \{ I(t-1), I(t-2), \ldots, I(t-N) \}
\]

where
\[
I(t-i) = \{ f_1(t-i), f_2(t-i), \ldots, f_d(t-i) \}, \ i=1,\ldots, N
\]

Generation of the output class is done based on the identification of stock trends. According to (Nair, Mohandas and Sakthivel, 2010), (Nair, Dharini and Mohandas, 2010) and (Nair, Mohandas and Sakthivel, 2011), a stock is said to be in an uptrend, if its price at time ‘t’, denoted by \( x(t) \) satisfies the following criteria:

1. \( x(t) > MA_t(25) \)
2. \( MA_t(25) > MA_t(65) \)
3. \( MA_{t+i}(25) > MA_{t+i-1}(25) \) for \( i=1,2,3,4 \)
4. \( MA_t(65) > MA_{t-1}(65) \)

where, the ‘n’ day moving average is represented as

\[
MA_t(n) = \frac{1}{n} \sum_{i=0}^{n-1} x(t-i)
\]

Similarly, a stock is said to be in a downtrend if

1. \( x(t) < MA_t(25) \)
2. \( MA_t(25) < MA_t(65) \)
3. \( MA_{t+i}(25) < MA_{t+i-1}(25) \) for \( i=1,2,3,4 \)
4. \( MA_t(65) < MA_{t-1}(65) \)

If the stock is neither in an uptrend nor in a downtrend, it is said to be exhibiting no trend.

Now, if at time ‘t’, the trend is either uptrend or no trend, output class at time ‘t’ is denoted by \( O(t) = \text{‘Trade’} \) and if the trend is down, output class at ‘t’ is denoted by \( O(t) = \text{‘No Trade’} \).

However, the system designed to be predictive in nature. To incorporate predictive capability into the system, the proposed system is designed to recommend the next day’s trading strategy.
This is accomplished by shifting the decision variable by one day. The output class vector is then represented as:

\[ O = \{ O(t), O(t-1), \ldots, O(t-(N-1)) \} \]  \hspace{1cm} (5.3)

The decision table, then can be represented by an \( N \times (d+1) \) table of the form \([I_{info}, O]\).

and each sample in the decision table can be represented as

\[ \{I(t-i), O(t-i+1)\} \text{ where } 1 \leq i \leq N \] \hspace{1cm} (5.4)

This decision table is then used for the purpose of feature selection and subsequent generation of trading recommendations. The proposed recommender systems differ from each other based on the feature selection technique used and the technique used for generating the trading recommendations; however, the samples in the initial decision table for all the proposed recommender systems can be represented using equation 5.4.

### 5.4 Performance Measures

A total of twelve different performance measures are considered with eight performance measures, namely, TP, AP, P/ST, L/LT, MD, TT, PF and WR indicating the performance of the system from an economic viewpoint and the remaining performance measures, namely, accuracy in percentage (AC), precision (PRE), sensitivity (SEN) and specificity (SPE), indicating the performance of the recommender classifier. Performance measures used in the present study are selected due to their widespread use in the field of financial forecasting, as observed from the literature survey of over a hundred publications in the field of financial forecasting, presented in (Nair and Mohandas, 2014) and as per recommendations made in (Brabazon and O’Neill, 2006). Similar measures of economic performance have also been employed in (Nair, Mohandas and Sakthivel, 2011) and (Nair et al., 2013). It must be noted that the parameter- maximum drawdown is defined as the worst performance by the system. In cases where trading generates both profits and losses, the worst loss is presented as the maximum drawdown. In case the trading does not generate any losses, the minimum profit generated by the system is presented as the maximum drawdown.
5.5 System Design

The generic block diagram of the classifier based stock trading recommender system as proposed in this chapter is presented in Figure 5.1. The two recommender systems presented in this chapter differ in the techniques used for feature selection and the classifiers employed.

The trading recommender system works as follows: first the dominant cycle length ‘\( L \)’, is identified from historical stock price data (of length=\( N \) samples) input to the system. A trial-and-error procedure is then followed by selecting subsets of the original dataset composed of multiples of \( L \), denoted by \( M \), such that \( L \times M \leq N \). Technical indicators and the corresponding one-day ahead trading recommendation vector are computed for these subsets according to the technique presented in section 5.3. It can be observed that considering only ‘\( L \)’ samples for training the classifier results in extremely poor classification performance, primarily due to the fact that the number of samples are insufficient for the classifier’s learning process. Hence, to increase the number of samples for training the classifier, subsets of the original datasets of size \( L \times M \) samples (where \( M \) is an integer multiple of \( L \)) are considered. In the next step, selection of the optimal set of technical indicators and their parameters is carried out with the help of a GA-optimized decision tree. The objective function is the maximization of profit factor, which is the ratio of sum of all the profits generated from the profitable trades and the sum of all the losses generated in loss-making trades. Hence, the optimization works in such a way that the number of profitable trades is maximized while at the same time minimizing the number of loss making trades. The technical indicator parameters are variables, which need to be optimized using the GA. Once the optimization process is completed, the resulting final population will consist of optimal technical indicator parameters (the technical indicator parameters that generate the highest profit factor for the given dataset). The features thus obtained using these optimal indicators are then subjected to feature selection thereby eliminating redundant/spurious features. Once the feature selection process is completed, the relevant optimal subset of technical indicators along with the one-day ahead trading recommendation consisting of \( M_{\text{opt}} \times L \) samples, represented by \( \{ I_{\text{train}}, O_{\text{train}} \} \) is used to train the classifier. On completion of the training phase, the out-of-sample performance of the classifier based recommender is validated on the test inputs \( I_{\text{test}} \) consisting of \( L \) samples. As can be seen from Figure 5.1, GA and decision tree are common
to all the classifier based trading recommender systems. The GA and decision tree parameters employed in this study are given below.

5.5.1 GA Parameters

Objective function: max (PF)
Reproduction technique: Elitism

5.5.2 Decision tree Parameters

Splitting criterion: Gini’s diversity index.
Minimum number of observations in impure node to be considered for splitting: 10
Minimum number of observations for leaf node: 1

5.5.3 Trading rule

For all the recommender systems, trading rule used is:

Trading rule

IF Next day’s recommendation = ‘Trade’ AND no stock bought, THEN Buy 1 unit of stock at next day’s opening price.
IF Next day’s recommendation = ‘No Trade’ AND stock already bought, THEN sell at next day’s opening price.
IF stock bought AND stock not sold till the penultimate day THEN sell at last day’s opening price.

END

It is also considered that if there is only uptrend in the entire training dataset, then stock should be bought at the opening price on the first day of the test data duration and held till the last day of the test set duration. For each trade, a transaction cost of 0.5% is considered. Two classifier based recommender systems are presented in this chapter. The description of each of the systems is given below.
Figure 5.1 The generic classifier based recommender system block diagram
5.5.4 GA-optimized Technical Indicators-Decision Tree-SVM Trading Recommender

The first recommender system considered in the present study employs decision trees for feature selection. The process is as follows: decision table generated using the optimal technical indicator parameters is used to generate a decision tree. The tree thus obtained, is composed of only those technical indicators that are relevant for the purpose of generating one-day-ahead trading recommendations. The decision table is now pruned by removing the features which do not form a part of the tree. The pruned decision table is now used to train the classifier. The classifier used in the present study is SVM trained using Sequential minimal optimization (SMO) (Platt, 1998) with $5^{th}$ order polynomial kernel, for all the datasets (empirically found to be consistently the best for all datasets under consideration).

After the training process is completed, the classifier can generate trading recommendations for the given input. Three variants of the proposed recommender system are evaluated (abbreviations in brackets alongside the variants denote the labels used in fig 4.2-4.5 to represent the corresponding recommender system performance):

a. GA optimized technical indicator-decision tree based recommender system (GA-TI-DT).

b. GA optimized technical indicator-decision tree –SVM based recommender system without feature selection (SVM No FS).

c. GA optimized technical indicator-decision tree –SVM based recommender system with decision tree based feature selection (SVM FS).

The performance of the proposed system was compared to the following five other trading systems:

1. GA optimized technical indicator-decision tree –Naïve Bayes based recommender system without feature selection (NB No FS).

2. GA optimized technical indicator-decision tree –Naïve Bayes based recommender system with decision tree based feature selection (NB FS).

3. GA optimized technical indicator-decision tree –ANN based recommender system with without feature selection (ANN No FS).

4. GA optimized technical indicator-decision tree –ANN based recommender system with decision tree based feature selection (ANN FS).
5. GA optimized technical indicator-decision tree –cANTMiner based recommender system with decision tree based feature selection (cANT FS).

6. Traditional B&H strategy (B&H).

The B&H strategy is realized by buying stock at the opening price on the first day of the given time frame and selling the stock at the closing price on the last day of the time frame. In this case too, a transaction cost of 0.5% is considered.

5.5.4.1 Results

Performance of all the recommender systems considered are evaluated based on the twelve measures listed in section 5.4. Results are presented in tables C.2-C.49 in the Appendix C. Overall profits generated by the proposed recommender system along with the performance of other recommenders considered are presented in Figs.5.2-5.5 below. The in-sample profits for HUL and Cipla over the three time frames is presented in Figure 5.2 while the in-sample profits for GSK and RBS over three time frames is presented in Figure 5.3. Out-of-sample results for HUL and Cipla are illustrated in Figure 5.4 and for GSK and RBS, the out-of-sample profits are shown in Figure 5.5. In the figures below, the label ‘No FS’ indicates the recommender system profits when no feature selection is performed. The label ‘FS’ indicates the recommender system profits with feature selection.
Figure 5.2 GA – optimized TI-DT based recommender systems in-sample profits for time frames 1-3: HUL (a)-(c) & Cipla (d)-(f)
Figure 5.3 GA optimized TI-DT based recommender systems in-sample profits for time frames 1-3: GSK (a)-(c) & RBS (d)-(f)
Figure 5.4 GA optimized TI-DT based recommender systems out-sample profits for time frames 1-3: HUL (a)-(c) & Cipla (d)-(f)
Figure 5.5 GA optimized TI-DT based recommender systems out-sample profits for time frames 1-3: GSK (a)-(c) & RBS (d)-(f)
5.5.5 GA Optimized Technical indicator-decision tree-SVM-cANTMiner recommender system

The second stock trading recommender system proposed in this study employs SVM for selecting the optimal feature set to be used for generating one-day-ahead trading recommendation (Nair, Mohandas and Sakthivel, 2011). In this recommender system, the optimal technical indicator parameters are identified using GA-decision tree. Once the optimal parameters are identified, a linear SVM based method for selecting the features (Brank et al., 2002) is employed. A general description of the linear SVM based feature selection is presented below.

When the data instances are described by vectors \( I(t) = \{f_1(t), f_2(t), \ldots, f_d(t)\} \), then, the class predictor trained by SVM has the form given in equation (5.5)

\[
\text{Prediction} (I(t)) = \text{sgn}[b + \sum a_i K(I(t), I(t-i))] \tag{5.5}
\]

Where \( K(I(t), I(t-i)) \) is the kernel function.

In the case of a linear kernel, \( K(I(t), I(t-i)) = I(t)^T I(t-i) \)

Thus, equation (5.5) can be rewritten as

\[
\text{sgn}[b + w^T I(t)] \text{ for } w = \Sigma_i a_i I(t-i) \tag{5.6}
\]

Where the vector of weights \( w = (w_1, \ldots, w_d) \) can be computed and accessed directly. Geometrically, the predictor uses a hyperplane to separate the positive from the negative instances, and \( w \) is the normal to this hyperplane.

In the feature selection approach used in the present study, the absolute value \( |w_j| \) is used as the weight of a feature \( j \). The features for which the value of \( |w_j| \) exceeds a threshold are retained. Features with small values of \( |w_j| \) do not have a large influence on the predictions of the classifier based on \( w \); and can be considered as not important for classification purposes and hence, eliminated. A feature may be considered important if it significantly influences the width of the margin of the resulting hyperplane; the margin being inversely proportional to \( ||w|| \), the length of \( w \). Since \( w = \Sigma a_i I(t-i) \) for a linear SVM model, \( ||w||^2 \) can be regarded as a function of the training vectors \( I(t-1), \ldots, I(t-N) \), and hence, the influence of feature \( j \) on \( ||w||^2 \) can be evaluated by finding the absolute values of partial derivatives of \( ||w||^2 \) with respect to \( f_j(t-i) \). For the linear kernel, it is observed that
where the sum is over support vectors and \(k\) is a constant independent of \(j\). Thus the features with higher \(|w_j|\) are more influential in determining the width of the margin.

In this study, the feature \(f_j\) is selected if \(p_j = 100 \frac{|w_j|}{\sum_{k=1}^{d} |w_k|} \geq 2\). Here \(1 \leq j \leq d\). The value of \(p_j\) is chosen to be \(\geq 2\) based on the results reported in (Nair, Mohandas and Sakthivel, 2011).

Once the optimal feature set has been identified, cANTMiner (Nair, Mohandas and Sakthivel, 2011) classifier is used to identify one-day-ahead trading recommendations. Performance of the proposed system is compared to five other recommender systems and the traditional B&H strategy. Other recommender systems considered are (the abbreviations alongside indicate the labels used for representing the recommenders in Figures 5.6-5.9):

1. GA-Technical indicator-decision tree-cANTMiner recommender without feature selection (cANT No FS)
2. GA-Technical indicator-decision tree-SVM-ANN recommender (ANN 2% FS)
3. GA-Technical indicator-decision tree-ANN recommender without feature selection (ANN No FS)
4. GA-Technical indicator-decision tree-SVM-Naïve Bayes recommender (NB 2% FS)
5. GA-Technical indicator-decision tree- Naïve Bayes recommender without feature selection (NB No FS)

The proposed recommender system is represented in Figure 5.6-5.9 as (cANT 2% FS). The performance of each of the recommender system is validated using the twelve performance measures discussed in section 5.4. Results are tabulated in tables C.14-C.25 in appendix C. In-sample profits for HUL and Cipla over the three time frames are presented in Figure 5.6, while the in-sample performance for GSK and RBS are illustrated in Figure 5.7. Figure 5.8 and 5.9 present the out-of-sample profits over the three time frames for Cipla, HUL and GSK, RBS respectively.
Figure 5.6 GA optimized TI-DT-SVM feature selection based recommender systems in-sample profits for time frames 1-3: HUL (a)-(c) & Cipla (d)-(f)
Figure 5.7 GA optimized TI-DT-SVM feature selection based recommender systems in-sample profits for time frames 1-3: GSK (a)-(c) & RBS (d)-(f)
Figure 5.8 GA optimized TI-DT-SVM feature selection based recommender systems out-of-sample profits for time frames 1-3: HUL (a)-(c) & Cipla (d)-(f)
Figure 5.9 GA optimized TI-DT-SVM feature selection based recommender systems out-sample profits for time frames 1-3: GSK (a)-(c) & RBS (d)-(f)

5.6 Technical indicator based trading

The results generated using the proposed recommender systems are compared with those produced by the technical indicators whose parameters have not been optimized. From the technical indicators considered in this study, twelve different trading signals are generated. The signals are
generated for UO, PVO, EM, the Ulcer index, PRoC, Bollinger, MACD, RSI, stochastics, PVI, NVI and William’s %R. The trading signals are generated as follows:

UO:
Buy at time t+1 if UO (t) < UO(t-1) AND UO(t) < 30
Sell at time t+1 if UO(t) >= 60 and UO(t-1) < 70

PVO:
Buy at time t+1 if (n-period MA of PVO(t-2) >= PVO(t-2)) AND (n-period MA of PVO(t-1) < PVO(t-1)) AND (n-period MA of PVO(t) < PVO(t))
Sell at time t+1 if (n-period MA of PVO (t-2) < = PVO(t-2)) AND (n-period MA of PVO(t-1) > PVO(t-1)) AND (n-period MA of PVO(t) > PVO(t))

EM:
Buy at time t+1 if EM(t-1)<0 AND EM(t)>0
Sell at time t+1 if EM(t-1)>0 AND EM(t)<0

Ulcer:
Buy at time t+1 if (Ulcer(t-1)>m-period moving average of Ulcer(t-1)) AND (ulcer(t) <= m-period moving average of Ulcer (t))
Sell at time t+1 if (Ulcer(t-1)<m-period moving average of Ulcer(t-1)) AND (ulcer(t) >= m-period moving average of Ulcer (t))

PRoC:
Buy at time t+1 if (PROC(t-1) < 0) AND (PROC(t) > 0)
Sell at time t+1 if (PROC(t-1) > 0) AND (PROC(t) < 0)

Bollinger:
Buy at time t+1 if (stock closing (t-1) < Bollinger lower band(t-1)) AND (stock closing (t) > Bollinger lower band (t))
Sell at time t+1 if (stock closing (t-1)>Bollinger upper band(t-1)) AND (stock closing (t) < Bollinger upper band (t))

MACD:
Buy at time t+1 if (p-period EMA of MACD (t-1) >= MACD(t-1)) AND (p-period EMA of MACD (t) <= MACD(t))
Sell at time t+1 if (p-period EMA of MACD (t-1)<=MACD(t-1)) AND (p-period EMA of MACD (t) >= MACD(t))
RSI:
Buy at time t+1 if \((\text{RSI}(t-1) > 30) \text{ AND } (\text{RSI}(t) \leq 30)\)
Sell at time t+1 if \((\text{RSI}(t-1) \leq 70) \text{ AND } (\text{RSI}(t) > 70)\)

Stochastics:
Buy at time t+1 if \((\%D(t-1) \geq \%K(t-1)) \text{ AND } (\%D(t) \leq \%K(t))\)
Sell at time t+1 if \((\%D(t-1) \leq \%K(t-1)) \text{ AND } (\%D(t) \geq \%K(t))\)

PVI:
Buy at time t+1 if \((\text{PVI}(t) > \text{one-year MA of closing price}(t-1)) \text{ AND } \text{PVI}(t-1) \leq \text{one-year MA of closing price}(t-1)\)
Sell at time t+1 if \((\text{PVI}(t) < \text{one-year MA of closing price}(t-1)) \text{ AND } \text{PVI}(t-1) > \text{one-year MA of closing price}(t-1)\)

NVI:
Buy at time t+1 if \((\text{NVI}(t) > \text{one-year MA of closing price}(t-1)) \text{ AND } \text{NVI}(t-1) \leq \text{one-year MA of closing price}(t-1)\)
Sell at time t+1 if \((\text{NVI}(t) < \text{one-year MA of closing price}(t-1)) \text{ AND } \text{NVI}(t-1) > \text{one-year MA of closing price}(t-1)\)

William’s %R:
Buy at time t+1 if \(\text{William’s \%R}(t-1) > -80 \text{ AND } \text{William’s \%R}(t) < -80\)
Sell at time t+1 if \(\text{William’s \%R}(t-1) > -20 \text{ AND } \text{William’s \%R}(t) < -20\)

For each of these indicators, at time ‘t’, if neither a Buy nor a Sell signal is generated, then a Hold signal is generated, which indicates that no trading should take place at t. At any given instant of time, any of the three signals- Buy, Hold or Sell may be generated by the indicators independent of each other. The practice used traditionally is to find what the majority of the indicators indicate and then follow the majority vote.

Trading performance of each indicator separately and with majority voting along with mutual information based selection of trading signals is evaluated on eight of the twelve performance measures discussed in section 5.4. Remaining four performance measures can only be computed for a classifier based system and hence are not considered in this case. The results are presented in Tables C.26-C.49 in Appendix C. In Tables C.26-C.49, the column labeled ‘voting’ implies the results of following this majority voting principle. It must be noted that since there is no ‘learning’
happening when technical indicators alone are used, the terms in-sample and out-of sample do not signify much meaning. However, in tables C.26-C.49, the terms in-sample data and out-of sample data have been used to indicate the corresponding time frame used (which can be identified by referring to Table 5.1). It must also be noted that since trading decisions have to be generated by indicators alone, only those indicators that can generate overbought/oversold (sell/buy) signals have been considered (in tables C.26-C.49). The B&H results are presented as well.

In tables C.26-C.49, the trading signals are generated by setting all the technical indicator parameters to the values as recommended in (Achelis, 1995) and (Eng, 1988). This was done to simulate the behavior of a novice trader who is not an expert in trading using technical indicators and is just following the herd by employing the most commonly used parameters for generating the indicators. The results of selecting trading signal using mutual information (column labeled ‘MI’ in tables C.26-C.49) and the selection of the trading decision based on majority voting are also presented in tables C.26-C.49. Using mutual information based feature section, those indicators, whose trading signals have more than 75% mutual information with respect to other trading signals, are eliminated. Remaining indicators take part in majority voting to identify the majority trading recommendation.

Profits generated for all the out-of-sample timeframes for all the stocks considered for technical indicator based trading are presented in Figure 5.10 (HUL and Cipla) and Figure 5.11 (GSK and RBS). The results of majority voting are labeled ‘Voting’ and those from mutual information are labeled ‘MI’.
Figure 5.10 TI based trading out-sample profits for time frames 1-3: HUL (a)-(c) & Cipla (d)–(f)
Figure 5.11 TI based trading out-sample profits for time frames 1-3. GSK (a)-(c) and RBS (d)-(f)

5.7 Conclusions

From the results, it can be observed that classifier based recommender systems tend to outperform the traditional B&H strategy and technical indicator based trading strategy. It is also observed that feature selection does tend to improve the performance of classifier based recommender systems. Of all the recommender systems considered, the GA-technical indicator-decision tree-SVM based stock trading recommender system with decision tree based feature
selection outperforms other recommender systems over majority of the out-of-sample time frames considered. It is also observed that the SVM based feature selection technique discussed in section 5.5.5 also results in improvements in the overall profits generated when compared to those generated by recommender systems operating without feature selection.

Classifier based recommender systems simplify the recommendation process by eliminating the need for the stock trader (a lay-man) to learn technical analysis and identify trading rules based on his/her expertise. The two systems proposed in this chapter utilize technical indicators, optimize the technical indicator parameters, select the relevant technical indicators and generate ‘trade’ or ‘no trade’ recommendations for the next trading day. Thus, by working at a high level of abstraction (as far as the end user is concerned), the proposed systems simplify the stock trading recommendation process for the inexperienced trader. Another major feature of the proposed systems is that they cast the problem of forecasting one-day-ahead stock price movement using historical data, which typically is considered from the viewpoint of time series forecasting, into a classification problem, where the recommender generates one-day-ahead trading recommendation as one of the two possible classes: trade or no trade. From the results, it can be said that classifier based stock trading recommender systems are quite effective in generating returns higher than those possible by the benchmark B&H strategy and the technical indicator based trading strategy.